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Supply chain design under uncertainty for advanced biofuel production based on bio-oil gasification

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Keywords

stochastic programming, bio-oil gasification, supply chain design

Disciplines

Industrial Engineering | Systems Engineering

Comments

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1. Introduction

As a potential substitute for petroleum-based fuel, biofuels are playing an increasingly important role due to their economic, environmental, and social benefits. However, the 2007-2008 global food crisis was claimed to be related to biofuels production [1] and this food vs. fuel debate set barriers for fi generation biofuels from consumable grain or lipid. On the other hand, second generation biofuels are produced from nonedible plant residues or dedicated energy crop, such as corn cobs, corn stover, switchgrass, miscanthus, and woody biomass. As a result, the feedstocks for second generation biofuels are less land and water intensive, which will not result in signifi t negative impact on the food market [2]. According to the revised Renewable Fuel Standard (RFS2) established in 2007, at least 36 billion gallons per year of renewable fuels will be produced by 2022 in the U.S., of which at least 16 billion gallons per year will be from cellulosic biofuels [3]. However, the targeted cellulosic biofuel volume requirement for 2013 was revised to be only 14 million gallons, which is significantly lower than the original target. This is mainly due to the high capital investment and logistic challenges in cellulosic biofuel. The supply chain activities of harvest, collection, storage, preprocessing, handling, and transportation dealing with uncertainties represent one of the biggest challenges to the cellulosic biofuels industry. Thus, it is timely and meaningful to study the economic feasibility of the commercialization of cellulosic biofuel considering the supply chain design under uncertainties.

Biomass can be converted to transportation fuels through a variety of production pathways, including biochemical and thermochemical platforms. One example of biochemical pathways is the corn ethanol production from fermentation. On the other hand, thermochemical conversion of biomass to produce transportation fuels has recently moved to the forefront of biofuel research and development. Fast pyrolysis and gasification are two of the most prominent technologies for thermochemical conversion of cellulosic biomass.

Fast pyrolysis thermally decomposes organic compounds in the absence of oxygen process, and the products include bio-oil, bio-char, and non-condensable gases [4]. The fast pyrolysis reactors typically run at temperature between 400 °C and 600 °C and can produce approximately 70% (by weight) bio-oil [5]. The other 30% is split between non-condensable gases (e.g., carbon dioxide or methane) and bio-char. The non-condensable gases and bio-char could be combusted to provide heat for the facility. In addition, bio-char is mostly organic carbon which can be sequestered or gasified to produce syngas [6]. Bio-oil has three to fi e times the energy density compared to raw biomass [7]. However, due to the high viscosity and acidity, bio-oil needs to be upgraded to be used as transportation fuels. The bio-oil upgrading has proven to be a challenging process due to the low conversion efficiency and fuel quality. On the other hand, biomass gasification runs at much higher temperature (800 $^{\circ}$C-1300 $^{\circ}$C) and it is a relatively mature technology. The syngas produced from the biomass gasification process will typically go through the Fischer-Tropsch synthesis to produce liquid transportation fuels [1]. However, commercialization of biomass gasification has been hampered by its high capital and operating costs due to the challenges of transporting bulky solid biomass over a long distance, processing solid feedstock at high pressure, and removing contaminants from the product gas stream. The techno-economic analysis of biomass gasification by Swanson et al. claims that the minimum fuel selling price is $4-5 per gallon of gasoline equivalent and the capital investment requirement is $500-650 million for a 2000 metric ton per day facility [8].

It is thus necessary to reduce system cost and improve supply chain ef- fi to improve the economic feasibility and competitiveness of the advanced biofuel production pathways. To reduce feedstock transportation cost, it has been suggested that biomass can be converted to bio-oil via fast pyrolysis near the harvest sites, then the bio-oil can be transported to the upgrading plant for transportation fuels production [9]. In this paper, the proposed hybrid production pathway is to combine the two prominent thermochemical production pathways. Biomass fast pyrolysis produces bio-oil in relatively small processing plants at distributed locations so that the transportation of bulky biomass over a long distance can be avoided. After mild hydrotreating, the bio-oil is then transported to a centralized gasification facility to produce transportation fuels. It should be recognized that centralized plant has advantages such as economies of scale, the inventory buff storage reduction, and administration overhead cost savings [10].

One of the biggest challenges of advanced biofuel production industry is the design of supply chain networks under uncertainties. There is a rich literature on supply chain network design. Shah reviewed the previous studies in modeling, planning, and scheduling with some real world examples to summarize the challenges and advantages of supply chain optimization [11]. An et al. compared the supply chain research on petroleum-based fuel and biofuel [12]. Eksioglu et al. formulated a model to determine the numbers, locations, and capacities of the biorefi conducted a case study for Mississippi in the U.S. to illustrate and verify the optimization model [13]. Nixon et al. used goal programming model to deploy the pyrolysis plants supply chain in Punjab, India [14]. Most of the literature on biofuel supply chain design assumes all the parameters in the system are deterministic. However, the biofuel industry is highly affected by the uncertainties along the supply chain such as biomass supply availability, technology advancement and biofuel price. For example, the biomass feedstock supply is highly dependent on biomass yield and farmers' participation. As a result, it is of vital importance to design the biofuel supply chain considering the uncertainties along the supply chain. Kim et al. considered a two-stage stochastic model using bounds of the parameters to determine the capacities and locations of the biorefi [15]. Alex et al. formulated a mixed integer linear programming model to determine optimal locations and capacities of biorefi [16]. Osmani et al. used stochastic optimization to deal with the uncertainties in biomass yield and price as well as biofuel demand and price [17]. As a recent advancement in the cellulosic biofuel technology, decentralized supply chain design for thermochemical pathways have not been studied extensively, especially scenario under uncertainties. This paper aims to provide a mathematical programming framework with a two-stage stochastic programming approach to design the supply chain network considering uncertainties along the supply chain. The production pathway under consideration is the bio-oil gasification, with bio-oil production from biomass fast pyrolysis at decentralized facilities and syngas production and fuel synthesis in the centralized gasification facility. This model provides methodological insights for the decision makers on the capital investment decisions and logistic decisions for the biofuel supply chain.

The remainder of the paper is organized as follows: in Section 2, the problem statement for the biofuel supply chain design is presented. Then, we discuss the deterministic mixed integer linear programming model and the two-stage stochastic programming models in Section 3. A case study of Iowa is conducted to illustrate and validate the optimization model in Section 4. Finally, we conclude the paper in Section 5 with a summary and potential research directions.

2. Problem Statement

As mentioned, one of the most important decisions faced by the biofuel industry is the design of the supply chain networks, especially under the system uncertainties. This provides the major motivation for this study.

The supply chain system schematics for the bio-oil gasification pathway are shown in Fig.1. Biomass is collected and consolidated at the county level. Biomass is then transported to the decentralized fast pyrolysis facilities to be converted to bio-oil. Mild-hydrotreated bio-oil is transported to the centralized gasification facility to produce the transportation fuels. It is assumed that each biomass feedstock supply location/county can serve multiple fast pyrolysis facilities; each fast pyrolysis facility can acquire feedstock from multiple biomass supply locations. The locations for the decentralized fast pyrolysis facilities and centralized gasification facility are assumed to be the centroids of counties.

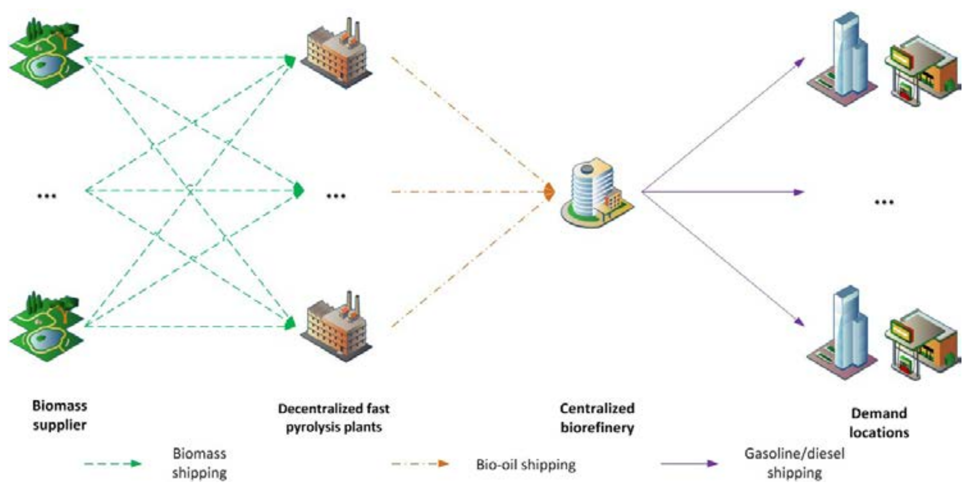

Figure 1: System schematics of supply chain

The supply chain network design of biofuel production is highly affected by the uncertainties along the supply chain such as biomass supply availability, technology advancement and biofuel price. The biomass supply availability is highly dependent on crop yields and farmers' participation; the conversion rates are affected by technology advancement and operating conditions; the biofuel price would change based on market conditions and enacted policies. Thus, it is of vital importance to make the supply network design decisions with the system uncertainties taken into consideration. Stochastic programming is one of the most widely used modeling frameworks to study the decision making under uncertainties.

The goal of this paper is to provide a two-stage stochastic programming framework for the biofuel supply chain optimization problem considering uncertainties. The comparison and analysis of the results provide methodological suggestions on the capital investment and logistic decisions. The insights derived from this study can contribute to the body of knowledge in decision making under uncertainties.

3. Model Formulation

The deterministic and stochastic models for this biofuel supply chain design problem are introduced. The objective is to maximize the annual profi for biofuel producers based on the hybrid production pathway of bio-oil gasi- fi The deterministic mixed integer linear programming model is fi introduced as a baseline model and then the two-stage stochastic model is presented to address the decision making under uncertainties. The stochastic programming framework bears the concept of recourse, which means some decisions (recourse actions) are taken after uncertainties have been realized. In other words, fi decisions are made by taking the factors' future effects into account. In the second stage, the actual values of the variables are realized and the corrective actions can be taken [18].

3.1. Mathematical notations

The mathematical notations are summarized in Table 1.

3.2. Deterministic model

In the deterministic mixed integer linear programming model, all the system parameters are assumed to be known with certainty.

3.2.1. Objective Function

The objective function is to maximize the annual profi for biofuel producers, which is defi as the revenue from selling the biofuels subtracted by the total system costs along the supply chain including the penalties. Penalties are imposed on the unmet demand which is based on the assumption that the producers have to purchase fuels from other sources to satisfy unmet demand. Penalties are also imposed for the surplus production due

Table 1: Notations for deterministic model

Subscripts		
i	$1,2,,I$	Biomass supply locations
j	$1,2,,J$	Candidate fast pyrolysis facility locations
k	$1,2,,K$	Biofuel demand locations
l	$1,2,,L$	Fast pyrolysis capacity levels
m	$1,2,,M$	Candidate refining facility locations
Decision Variables		
x_{ij}		Amount of biomass transported from supply location i to candidate fast pyrolysis facility location j
y_{jm}		Amount of bio-oil transported from candidate fast pyrolysis facility location j to candidate refining facility location m
z_{mk}		Amount of biofuels transported from refining facility location m to demand location k
a_{jl}		Whether a fast pyrolysis facility of capacity level l is planned at candidate facility location j (binary variable)
g_m		Whether a refining facility is planned at candidate refining facility location m (binary variable)
Parameters		
B		Total budget
C^{UP}		Capital cost of the centralized refining facility
C_l^{Cap}		Capital cost of the decentralized fast pyrolysis facility at capacity level l
P_k		Biofuels price at demand location k
D_k		Biofuels demand at demand location k
Pe_k		Penalty for the unmet demand at demand location k
Pe'_k		Penalty for the exceeded demand at demand location k
C_i^{Col}		Unit biomass collecting cost at supply location i
C^{MO}		Unit conversion cost from dry biomass to bio-oil
C^{OF}		Unit conversion cost from bio-oil to biofuels
C_{ij}^{BM}		Unit biomass shipping cost from supply location i to candidate fast pyrolysis facility location j
C_{jm}^{BO}		Unit bio-oil shipping cost from candidate fast pyrolysis facility location j to candidate refining facility location m
C_{mk}^{BF}		Unit biofuel shipping cost from candidate refining facility location m to demand location k
U_l		Capacity of fast pyrolysis facility at level l
V		Capacity of refining facility
A_i		Available biomass feedstock at location i
α		Sustainability factor
β		Conversion factor from wet biomass to dry biomass
γ		The loss factor of biomass during collection and transportation
θ_1		Conversion ratio, metric ton of bio-oil per metric ton of dry biomass
θ_2		Conversion ratio, metric ton of biofuels per metric ton of bio-oil
δ		Availability factor
n		Operation life for facilities in year
q		Interest rate

to additional inventory holding and storage costs. A variety of system costs have been considered in the model including facility capital investment cost, biomass collection cost, biofuel conversion cost, and logistic cost.

Firstly, the total capital cost for the decentralized fast pyrolysis facility at level l is $\sum_{j=1}^{J}\sum_{l=1}^{L} C_l^{Cap} a_{jl}$. With the assumption that the facilities have an n-year operation life and an interest rate of i, the annual amortized capital cost is $(i(i+1)^n)/((i+1)^n-1)\left(\sum_{j=1}^{J}\sum_{l=1}^{L} C_l^{Cap} a_{jl}+C^{UP}\right)$. Secondly, the cost of collection biomass from diff t feedstock location is $\sum_{i=1}^{I}\sum_{j=1}^{J} C_i^{Col} x_{ij}$. Thirdly, $C^{MO}(1-\gamma)\beta\sum_{i=1}^{I} x_{ij}$ is the fast pyrolysis conversion cost from biomass to bio-oil and $C^{OF}\sum_{j=1}^{J}\sum_{m=1}^{M} y_{jm}$ is the conversion cost from bio-oil to biofuel at the gasification and upgrading biorefinery. Lastly, the logistic costs include the biomass shipping cost from biomass feedstock locations to fast pyrolysis facility locations, the bio-oil shipping cost from fast pyrolysis facility locations to gasification and upgrading biorefi location, and the biofuel shipping cost from gasification and upgrading biorefi location to demand locations.

In sum, the objective function can be formulated as follows:

$$
\begin{aligned}
&max\zeta = income - penalty - cost \\
&= \sum_{k=1}^{K}\sum_{m=1}^{M}(P_k z_{mk}) - \sum_{k=1}^{K}\{(D_k - \sum_{m=1}^{M} z_{mk})Pe_k + (\sum_{m=1}^{M} z_{mk} - D_k)Pe'_k\} \\
&-\{\frac{(q(q+1)^n)}{((q+1)^n-1)}\left(\sum_{j=1}^{J}\sum_{l=1}^{L} C_l^{Cap} a_{jl} + C^{UP}\right) + \sum_{i=1}^{I}\sum_{j=1}^{J} C_i^{Col} x_{ij} \\
&+C^{MO}(1-\gamma)\beta\sum_{i=1}^{I} x_{ij} + C^{OF}\sum_{j=1}^{J}\sum_{m=1}^{M} y_{jm} + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{BM} x_{ij} \\
&+ \sum_{j=1}^{J}\sum_{m=1}^{M} C_{jm}^{BO} y_{jm} + \sum_{m=1}^{M}\sum_{k=1}^{K} C_{mk}^{BF} z_{mk}\}
\end{aligned}
$$

3.2.2. Constraints

The constraint (1) ensures that the sum of capital cost of decentralized fast pyrolysis facilities and centralized biorefi does not exceed the total budget.

$$B \geq C^{UP} + \sum_{j=1}^{J} \sum_{l=1}^{L} C_l^{Cap} a_{jl} \tag{1}$$

The total amount of biomass transported from supply location i to all the candidate fast pyrolysis facility locations should not exceed the available feedstock for each supply location as denoted in constraint (2). α is the sustainability factor which is the percentage of biomass that has to be left in the field to sustain the soil nutrients. δ is the availability factor which is defined as the ratio of the available biomass to collectable biomass. This factor represents the social factors that could impact the biomass availability for biofuels production such as farmers' willingness to participate [19].

$$\sum_{j=1}^{J} x_{ij} \leq (1-\alpha)\delta A_i, \quad \forall i \tag{2}$$

The facility capacity limits are included in the model in constraint (3) and constraint (4). The loss factor $\gamma \in [0,1)$ is the fraction weight loss of biomass during the collection, transportation, and unloading process and β is the conversion ratio from wet biomass to dry biomass on the weight basis.

$$\sum_{l=1}^{L} U_l a_{jl} \geq (1-\gamma)\beta \sum_{i=1}^{I} x_{ij}, \quad \forall j \tag{3}$$

$$V g_m \geq \sum_{j=1}^{J} y_{jm}, \quad \forall m \tag{4}$$

There should be no more than one fast pyrolysis facility in each candidate facility location illustrated in constraint (5). In addition, only one centralized refining facility will be constructed in one region of interest (typically one state) as denoted in constraint (6).

$$\sum_{l=1}^{L} a_{jl} \leq 1 \quad \forall j \tag{5}$$

$$\sum_{m=1}^{M} g_m = 1 \tag{6}$$

We assume that biomass is converted to bio-oil with conversion efficiency θ_1 and bio-oil is converted to biofuel with conversion efficiency θ_2 on the weight basis. Thus, we have the following conversion balance constraints (7) and (8):

$$(1-\gamma)\beta\theta_1 \sum_{i=1}^{I} x_{ij} = \sum_{m=1}^{M} y_{jm}, \quad \forall j \tag{7}$$

$$\theta_2 \sum_{j=1}^{J}\sum_{m=1}^{M} y_{jm} = \sum_{m=1}^{M}\sum_{k=1}^{K} z_{mk} \tag{8}$$

In summary, this mixed integer linear programming model aims to maximize the annual profit for biofuel producers considering the capital investments and logistic decisions. This deterministic model provides the baseline for the stochastic programming model in the next sections.

3.3. Two-stage stochastic programming model

Feedstock availability, fuel price, capital costs, logistic costs and technology advancement are among the most influential stochastic parameters along the biofuel supply chain [20]. These uncertainties can be incorporated into the stochastic modeling framework to assist the decision making.

In this study, biomass availability, technology advancement, and biofuel prices are selected as the stochastic parameter to be investigated.The stochasticity of the parameter are discretely distributed. We use subscript s to represent scenario with corresponding probability Pr_s and the subscript is also incorporated into the decision variables and parameters.

The two-stage stochastic programming model is formulated as follows:

$$\begin{aligned}
\max \zeta = &\frac{(q(q+1)^n)}{((q+1)^n-1)} \sum_{j=1}^{J}\sum_{l=1}^{L} (C_l^{Cap} a_{jl} + C^{UP}) + \sum_{s=1}^{S} Pr_s\{ \sum_{k=1}^{K}\sum_{m=1}^{M} (P_k z_{mks}) \\
&- \sum_{k=1}^{K} \{(D_k - \sum_{m=1}^{M} z_{mks}) Pe_k + (\sum_{m=1}^{M} z_{mks} - D_k) Pe'_k\} - \{ \sum_{i=1}^{I}\sum_{j=1}^{J} C_i^{Col} x_{ijs} \\
&+ C^{MO}(1-\gamma)\beta \sum_{i=1}^{I} x_{ijs} + C^{OF} \sum_{j=1}^{J}\sum_{m=1}^{M} y_{jms} + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{BM} x_{ijs}
\end{aligned}$$

$$+\sum_{j=1}^{J}\sum_{m=1}^{M} C_{jm}^{BO} y_{jms} \sum_{m=1}^{M}\sum_{k=1}^{K} C_{mk}^{BF} z_{mks}\}\}$$

s.t.

Constraints (1), (5), (6)

$$\sum_{j=1}^{J} x_{ijs} \leq (1-\alpha)\delta A_{is},\ \forall i,\ \forall s$$

$$\sum_{l=1}^{L} U_l a_{jl} \geq (1-\gamma)\beta \sum_{i=1}^{I} x_{ijs},\ \forall j,\ \forall s$$

$$V g_m \geq \sum_{j=1}^{J} y_{jms},\ \forall m\ \forall s$$

$$(1-\gamma)\beta\theta_{1,s} \sum_{i=1}^{I} x_{ijs} = \sum_{m=1}^{M} y_{jms},\ \forall j,\ \forall s$$

$$\theta_{2,s} \sum_{j=1}^{J}\sum_{m=1}^{M} y_{jms} = \sum_{m=1}^{M}\sum_{k=1}^{K} z_{mks},\ \forall s$$

$$x_{ijs},\ y_{jms},\ z_{mks} \geq 0,\ g_m \in \{0,1\},\ \forall i,j,k,m,l,s$$

The fi decisions involve variables which have to be decided before the uncertainties are realized. After the uncertainties are realized, the second-stage decisions are made. In this supply chain network design model, the fi decision variables include the binary variables a_{jl} and g_m, which make the capital investment decisions including the facility locations (decentralized fast pyrolysis and centralized refining facility) and capacities of the decentralized fast pyrolysis facilities. The second-stage decision variables x_{ijs}, y_{jms}, z_{mks} determine the biomass and biofuels fl ws.

Constraints (1), (5), and (6) are the fi st-stage constraints, these constraints remain the same in all scenarios and they are same as in the deterministic linear program model. The rest of the constraints change based on the stochastic scenario. Note that this model is a generic method to deal with uncertainties in a supply chain and can be adapted to other type of uncertainties and supply chains settings.

One of the most commonly used methods for scenario generation is moment matching method. This method aims to construct a set of scenarios with corresponding probability such that the statistical properties of the approximating distribution match the specified statistical properties based on historical data or reality. This is achieved by minimizing the diff between the statistical properties of the constructed distribution and the known specifications, subject to nonnegative probabilities that sum up to one [21].

4. Case study

We apply the supply chain design framework for a case study based on Iowa in the U.S. to illustrate and validate the optimization model. Iowa possesses the largest quantity of corn stover in the United States and has been one of the leading states of corn ethanol and soybean biodiesel production [22]. With the abundance of cellulosic biomass, Iowa has the potential in the cellulosic biofuel production via thermochemical conversion processes.

4.1. Data sources

The centroids of 99 counties of Iowa are chosen as candidate biomass (corn stover in this case study) supply locations, the potential sites for distributed fast pyrolysis facilities, and the candidate location for the centralized gasification facility. The annual corn stover yield is estimated based on corn grain yield with the residue harvest index of 0.5 meaning 50% of the above ground biomass is grain and the amount of corn stover is same as grain [23]. The weight of No. 2 fi corn at 15.5% moisture is applied to calculate the corn grain yields [24]. The county level corn production and yield data from 2003-2012 are collected from the National Agricultural Statistics Service (NASS), United States Department of Agriculture (USDA) [25]. The average county level corn stover yield in Iowa for 2003-2012 is shown in Fig. 2 with the darkness of the shade corresponding to the corn stove yield.

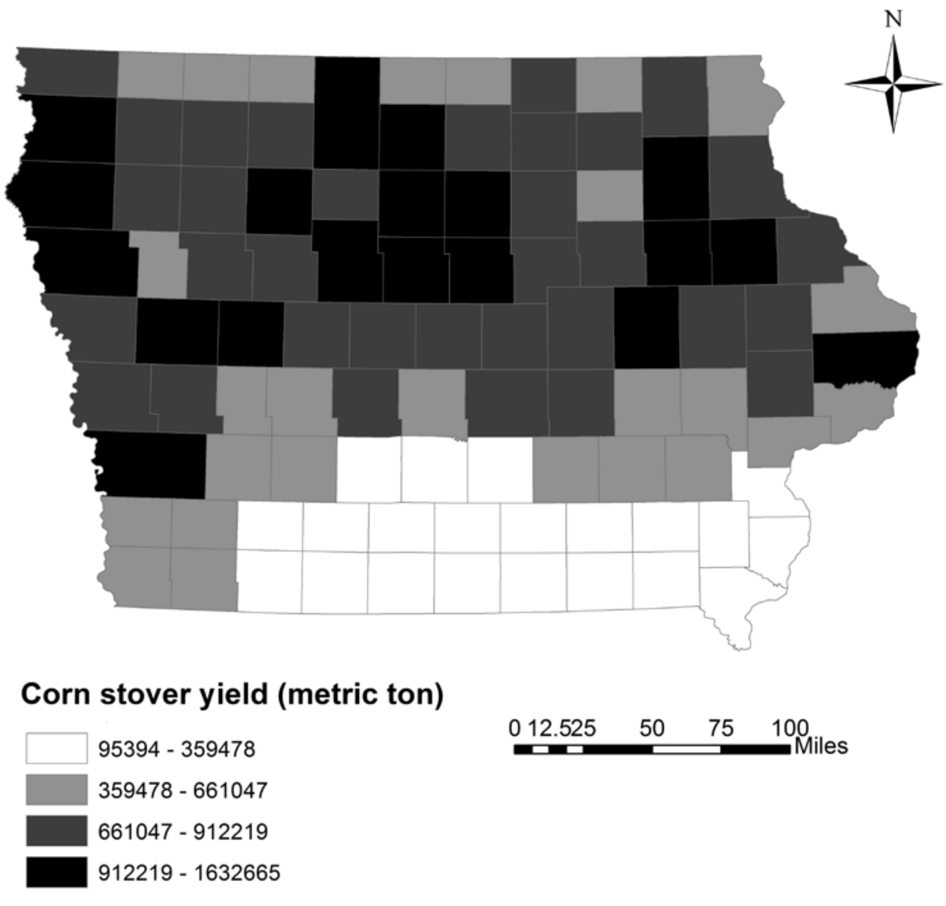

Figure 2: Average corn stover yield in Iowa (2003-2012)

In addition, the collectable corn stover is limited by growing conditions, soil nutrient levels, and method of harvest. Montross et al. reported the collection efficiencies of using three strategies in Kentucky: bale only to be 38%; rake and bale to be 55%; and mow, rake, and bale to be 64% [26]. Schechinger and Hettenhaus reported collection efficiencies of 40% to 50% without raking and 70% with raking in large-scale stover collection operations in Nebraska and Wisconsin [27]. Lindstrom suggested that a 30% removal rate would not significantly increase soil loss [28]. Papendick et al. later shows that a 30% removal rate results in 93% soil cover after residue harvest [29]. The National Resource Conservation Service (NRCS) suggests that a minimum of 30% of stover cover must remain in the fi to prevent soil erosion [30]. In this analysis, we assume the sustainability factor to be 0.3, which means at least 30% of the stover must be left in the fi to maintain soil health. In the base case scenario, the availability factor is assumed to be 0.4, and the impact of this availability factor on the supply chain design is also investigated in this study.

The collection cost for corn stover is diff t for each county due to the diff in collection quantities and collection methods. The collection cost estimation is based on the regression analysis from Graham et al. [31]. Biomass loss factor, which accounts for possible mass loss during loading, transportation, and unloading of the biomass, is assumed to be 0.05 in this analysis [32, 33].

The total gasoline demand of Iowa is based on the state-level gasoline consumption from the Energy Information Administration (EIA) [34]. Weekly retail gasoline prices for the Midwest area from 2003 to 2012 are also from EIA [35]. Gasoline demand of each demand area is assumed to be proportional to the population of metropolitan statistical areas (MSAs). The partitions and population information of Iowa MSAs are based on U.S. Census Bureau [36].

All the biomass suppliers, biorefi and demand locations are assumed to be at the county centroids. Transportation distances for biomass, bio-oil and biofuels are calculated using the great circle distance, which is defi as the shortest distance between the two locations on a sphere. In addition, the actual distances have been adjusted to account for the difference in the transportation methods by the circuit factors from the Congressional Budget Office [37].

The fi transportation cost of corn stover via truck is 5.34 \$/metric ton*miles and the variable cost of 0.23 \$/metric ton*miles [38]. The transportation cost of bio-oil via truck is assumed to be equal to the national average truck shipping cost of 0.312 \$/metric ton*miles based on Bureau of Transportation Statistics (BTS). The transportation cost of biofuel via pipeline is assumed to be equal to the national average oil pipeline cost, which is 0.032 \$/metric ton*miles [39]. The cost data have been adjusted for infl to the 2012 US dollars.

In the fast pyrolysis process, the biomass is converted into bio-oil (53-78%), char (12-34%), and gas (8-20%) [40]. The bio-oil yield is assumed to follow the normal distribution based on the experimental results from Iowa State University. In this study, the fl bed reactor is employed in the fast pyrolysis which has an average conversion ratio of 0.63 from biomass to bio-oil on weight basis [41]. The conversion ratio from bio-oil to biofuel is not available due to lack of experimental data. The bio-oil gasification yield are related to gasification agent and conditions [42]. Limited experiments show high carbon conversion of gasification but low efficiency from syngas to fuel. Raffelt et al. reported a conversion ratio of 0.156 on weight basis for slurry (80% bio-oil and 20% char) gasification [40]. We assume that the conversion ratio from bio-oil to biofuel follows a normal distribution with an average of 0.20 on weight basis. With these assumptions, the average fuel yield for the pathway under analysis would be 31.2 million gasoline gallon equivalent (GGE) per year for the plant size to of 2000 metric ton biomass per day facility. This is consistent with reported fuel yield of 29.3-58.2 million GGE per year for 2000 metric ton per day facility [43].

Wright et al. reported that the capital cost of centralized gasification plant with a capacity of 550 million GGE per year is about 1.47 billion [44]. The capital cost of distributed fast pyrolysis facility with a capacity of 2,000 metric ton per day is \$200 million [41]. The commonly used scaling factor of 0.6 (the ”sixth-tenth rule”) is applied to estimate capital cost for facilities with other capacity levels [45]. In this study, we consider three capacity levels of distributed fast pyrolysis facilities: 500, 1000, and 2000 metric ton per day. According to RFS2, at least 36 billion gallons per year of renewable fuels will be produced by 2022, which is about 28% of the national gasoline consumption. In this study, we assume the centralized gasification and upgrading plant has a capacity of 550 million GGE per year, which could satisfy more than 30% of the gasoline consumption in Iowa. Thus, we only need to consider one centralized bio-oil gasification and upgrading facility in this case study.

It is assumed that all the facilities have a 20-year operation life and an interest rate of 10% [20, 46]; the online time of all the facilities is 328 days per year (equivalent capacity factor of 90%). In the following two sections, the computational results of the biofuel supply chain design for both deterministic case and stochastic case are presented.

4.2. Analysis for the deterministic case

In the deterministic case, 17 distributed fast pyrolysis plants will be planned to be built, and all of them are at the highest capacity level (2000 metric ton per day). This is mainly due to the budget limit and economies of scale. The centralized gasification plant is planned to be located in Hamilton County to balance the bio-oil transportation cost and biofuel transportation cost. The optimal locations for these facilities are shown in Fig. 3. The shaded areas are biomass feedstock suppliers (71 counties) in this case. These counties are mainly located at the central and northern part of Iowa, which have a higher yield of corn and thus have better availability for corn stover. Several previous studies [33, 32] showed similar site selection decision but there are more biomass feedstock counties involved in our case. The counties locations of distributed fast pyrolysis plants illustrate the trade-off between biomass collection as well as transportation cost and bio-oil transportation cost.

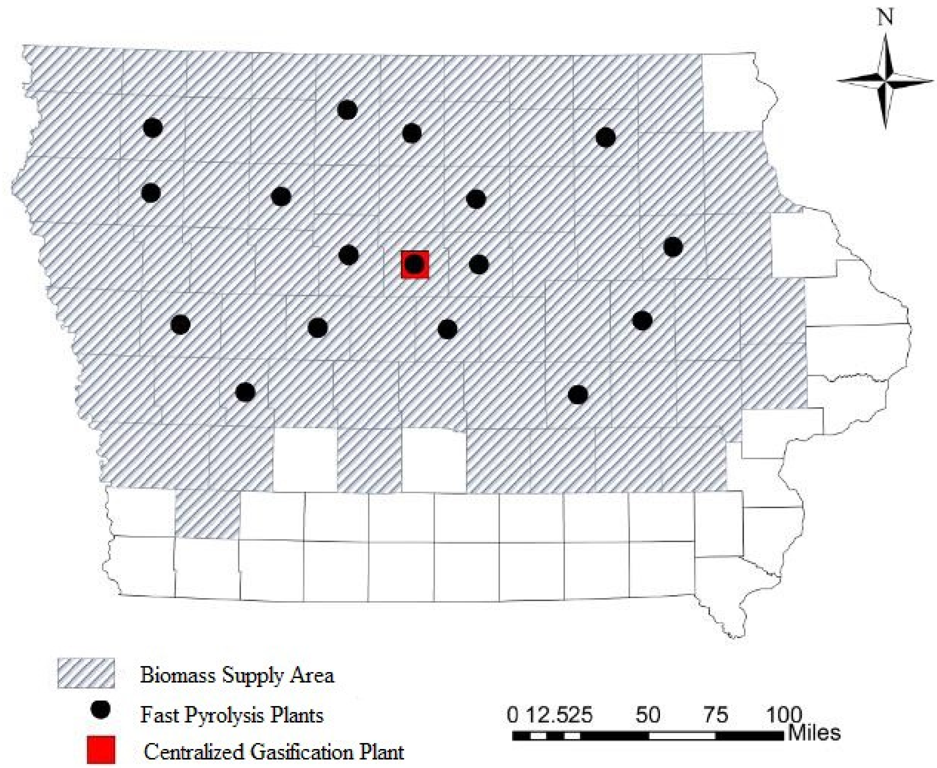

Figure 3: Optimal facilities locations in the deterministic case

In general, feedstock production and logistic constitute more than 35% of the total production cost of advanced biofuel [47] and logistic associated with moving biomass from farmland to biorefi can make up 50% to 75% of the feedstock cost [48]. Table 2 includes the annual itemized costs in the deterministic case. Total shipping cost accounts for 14% of the total cost; biomass collecting cost accounts for 18% of the total cost; total capital cost accounts for about 25% of the total cost; conversion cost accounts for 43% of the total cost. In the category of shipping cost, biomass shipping cost is the most significant (54%). These results are in consistent with the range reported in the literature [47, 48].

Table 2: Annual itemized costs in deterministic case (Million dollars)

Biomass collecting cost	416.93
Total capital cost	604.33
Capital cost of the centralized refining facility	184.06
Capital cost of the fast pyrolysis facility	420.27
Total shipping cost	334.04
Biomass shipping cost	181.99
Bio-oil shipping cost	146.80
Biofuel shipping cost	5.25
Conversion cost	1020.20
Total	2375.51

4.3. Analysis for the stochastic case

The uncertainties under considerations include biomass availability, technology advancements and biofuel price. Technology advancements uncertainty is represented by the probabilistic distribution of two conversion ratios. Historical data for corn stover yield and retail gasoline prices are available to estimate the distributions. In this case study, moment matching method has been employed to generate the probabilistic scenarios. Statistics such as mean, variance, skewness, and kurtosis are used for moment matching. This non-linear optimization problem is solved by applying a heuristic of changing initiating value until a satisfactory solution is obtained. The General Algebraic Modeling System (GAMS) is utilized to solve the moment matching problem and a scenario tree with a size of 16 is generated. A summary of scenarios in the stochastic model is included in Table 3.

Table 3: Scenario summary

	Pr.	Biomass Yield (metric ton/acre)	Gasoline Prices ($/Gallon)	Conversion Ratio θ_1	Conversion Ratio θ_2
1	0.0128	2.2066	2.2035	0.4961	0.1825
2	0.0114	2.1568	2.5758	0.4476	0.1810
3	0.1269	2.9174	2.4271	0.7770	0.2197
4	0.1130	3.1437	4.5391	0.6242	0.1993
5	0.1116	2.9115	4.4923	0.6243	0.1984
6	0.1078	2.9048	3.4381	0.6253	0.1959
7	0.1092	2.6570	3.5253	0.6229	0.2097
8	0.1255	2.9986	3.2187	0.6206	0.1963
9	0.0531	2.7582	3.3948	0.6198	0.1961
10	0.0100	2.1041	2.5689	0.3952	0.1875
11	0.0288	2.7502	3.3767	0.5742	0.1917
12	0.0164	2.6637	3.2652	0.5465	0.1925
13	0.0259	2.7056	3.3314	0.5897	0.1944
14	0.0143	2.6095	3.1129	0.5376	0.1945
15	0.1231	3.1086	4.0164	0.6265	0.1950
16	0.0100	2.0942	2.8036	0.3858	0.1562

In the stochastic case, 17 distributed fast pyrolysis plants are proposed, and all of them are at the highest capacity level. This is same as the deterministic case and indicates that the capacity levels are insensitive to uncertainties. The numbers of biomass feedstock sites (counties) involved in stochastic case are various based on scenarios with a maximum of 79 counties. Nine scenarios (with a total probability of 0.6) need biomass supply from more than 71 counties. The optimal locations for these facilities are represented in Fig. 4. The shaded areas are union set of the biomass feedstock sites involved in all the stochastic scenarios (81 counties).

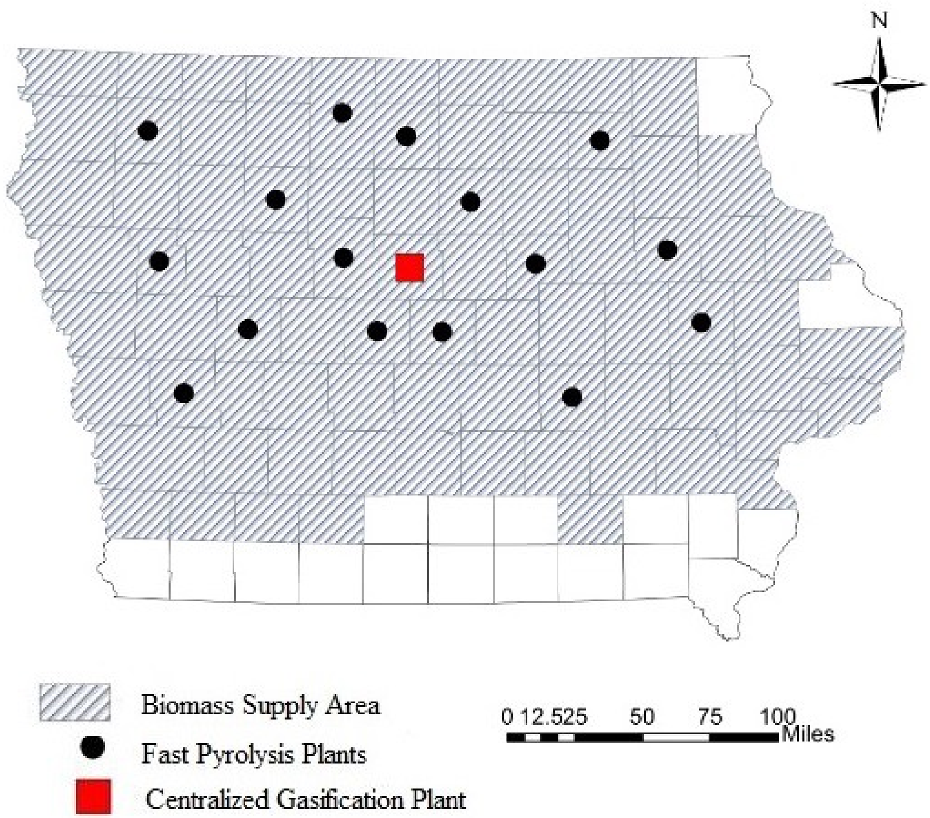

Figure 4: Optimal facilities locations in stochastic case

In both the deterministic and the stochastic cases, 17 distributed fast pyrolysis plants are proposed but they are not at the same locations. The plants are all proposed to be built at the highest capacity level which was found to be more cost effective due to the economies of scale, and this conclusion is consistent with previous literature [32, 46]. The centralized gasification plant will be constructed at the same site (Hamilton County) in both cases, which is located at the center of high corn yield counties.

Despite of the similarities of the both cases, diff exist for the supply chain network configurations. In the stochastic case, it is preferable to build the fast pyrolysis plants farther away from the centralized gasification and upgrading plant because biomass collection sites are more distributed due to the uncertainties in biomass feedstock supply availability. Thus, this supply chain network demonstrates the management of the trade-off between biomass availability and transportation costs.

The yearly profit in the deterministic case is 154.53 million dollars. For comparison, the numerical value of parameters used in deterministic case are the expected value of those parameters from the stochastic scenarios, thus this deterministic solution is also called the expected value solution (EV). The solution in the stochastic case is known as recourse problem solution (RP). In this case study, the yearly profi from the recourse problem is 129.57 million dollars. If we apply the decisions in deterministic case to the stochastic environment, we will get the expected yearly profi with the EV solution. This is called expected results of EV solution (EEV), which is 129.11 million dollars in this case study. The value of the stochastic solution (VSS) could be defi as $VSS = EEV - RP$. The VSS is about 0.46 million dollars, which is the direct economic benefit of considering uncertainties in the decision making process.

4.4. Discussion on the impact of farmers' participation

Although some literature has investigated the environmental consequences of biomass collection from the fi limited studies have taken the social factors such as farmers' willingness to participate into consideration. However, the farmers' willingness to participate makes a direct impact on the biomass feedstock availability. Recently, an Iowa farmer survey conducted by Tyndall et al. shows that only 17% of farmers in Iowa show interest in harvesting their stover and about 37% are undecided [22]. This survey showed that the farmers' environmental concerns such as water quality, soil moisture, wildlife habitat, and loss of nutrients (P, N, K) are the most important barrier for stover collection. On the other hand, farmers have the option to sell the biomass to the market for heating or electricity generation[49]. Therefore, biomass availability is directly related to the farmers' willingness to supply the cellulosic biomass. In this section, the impact of farmers' participation, which is represented as the availability factor δ in both the deterministic case and the stochastic case, is further discussed.

For the deterministic case, if the availability factor δ is less than 0.23, which means on average no more than 23% of the farmers would participate in corn stover collection, the objective function value is equal to zero. In this case, this biofuel supply chain system is not profi and it is optimal not to construct any facilities. When the availability factor δ is in the range of 0.23 to 0.36, the system is profi but it could not satisfy the biofuel production target of the entire state. The goal is to satisfy at least 30% of the gasoline consumption in Iowa, which is about 517 million GGE per year. Thus, at least 33000 metric ton dry biomass per day is needed at distributed fast pyrolysis plants. The biofuel supply target will be met if the availability factor δ is larger than 0.36.

Table 4 provides the annual itemized costs and profi for a variety of availability factor δ's. The total capital cost, biomass collection cost and total shipping cost increase when availability factor increases from 0.3 to 0.4. This is because of the increase of the facilities production and capacities. It should be noted that when the biofuel production capacity can meet the target biofuel demand, the total shipping cost and biomass collection cost will decrease as the availability factor increase. After that, the total capital cost will not change since the same number and capacities of facilities are planned. As a result, the yearly profit will increase as the availability factor increase. In summary, the system cost will decrease and yearly profi will increase with increase in the farmers' participation because there is more fl y in choosing the biomass suppliers and better decisions can be reached.

Table 4: Annual itemized costs and profits for different δ (Million dollars)

δ	0.3	0.4	0.5	0.6	0.7
Profit	69.246	154.53	200.92	232.09	256.43
Total capital cost	530.21	604.39	604.39	604.39	604.39
Biomass collecting cost	347.72	416.93	409.46	402.17	398.69
Total shipping cost	296.27	334.04	295.13	271.24	250.38
Conversion cost	840.14	1020.20	1020.20	1020.20	1020.20

Compare Figure 5 to Figure 3, it is observed that the locations of fast pyrolysis plants are more centralized when availability factor δ is equal to 0.7 and we only need 40 counties (rather than 71 when δ is equal to 0.4) to supply the biomass. These results not only illustrate the phenomena that the locations of fast pyrolysis plants are sensitive to uncertainties, but also suggest that the optimal supply chain decisions will be improved by increasing biomass availability due to the additional fl in choosing the biomass harvesting sites and consequently reduction of total system cost [32, 17].

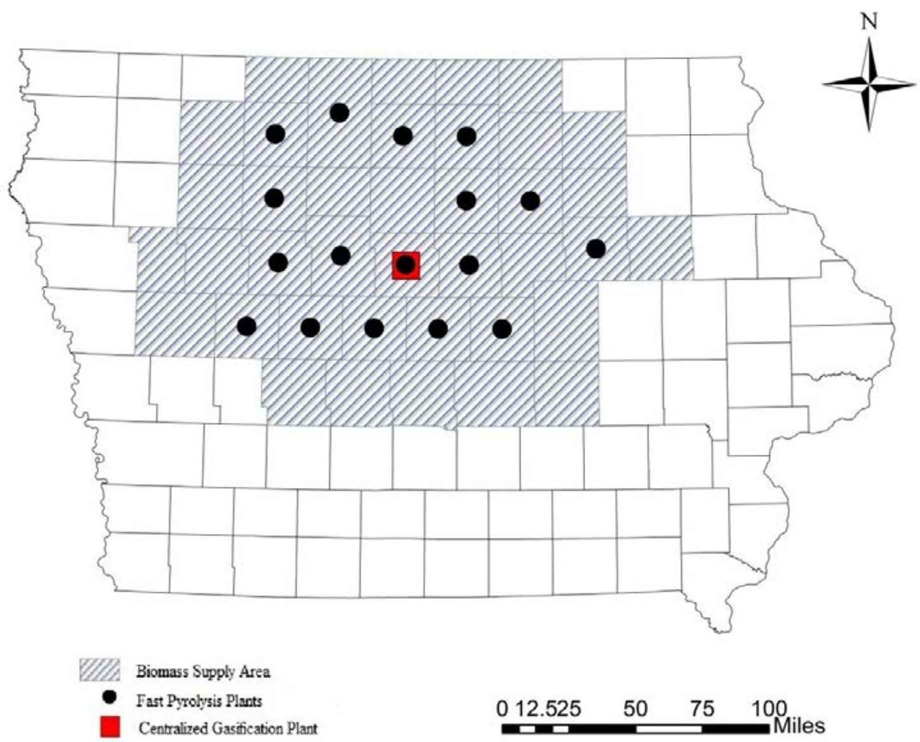

Figure 5: Optimal facilities locations in deterministic case ($\delta = 0.7$)

Table 5 shows the value of the stochastic solution (VSS) will decrease as the availability factor increase. The VSS will reduce to zero when the availability factor is larger than 0.5. It can be observed from the model that as farmers' participation increase in Iowa, the supply chain design and optimization model will become more robust. On the other hand, since the advanced biofuel industry is still at its infancy, the farmers' participation is currently at a relatively low level. Therefore, it is beneficial to apply stochastic programming framework to deal with the uncertainties and improve the decision making. This analysis provides the decision makers another insight to improve system resiliency by increasing farmers' participation.

Table 5: Stochastic programming results for different δ

δ	EV	RP	EEV	VSS
0.3	69.25	56.25	55.74	0.51
0.4	154.53	129.57	129.11	0.46
0.5	200.92	171.82	171.76	0.06
0.6	232.09	200.93	200.93	0
0.7	256.43	222.74	222.74	0

5. Conclusion

Cellulosic biofuels play an increasingly important role in meeting RFS2 and reducing energy dependence. The hybrid thermochemical production pathway of bio-oil gasification which combines fast pyrolysis and gasification is one of the promising production pathways for advanced biofuel production. In this production pathway, the widely distributed small-scale fast pyrolysis processing plants could avoid transporting bulky solid biomass over a long distance and the centralized gasification and fuel synthesis facility can take advantage of the economies of scales. Due to the significance of supply chain related system costs, the design of biofuel supply chain networks plays an essential role in the commercialization process.

This paper provides a mathematical programming framework with a two-stage stochastic programming approach to deal with the uncertainties in the biofuel industry. The fi st-stage makes the capital investment decisions including the locations and capacities of facilities while the second-stage determines the biomass and biofuels fl ws. This model is a generic method to deal with uncertainties in a supply chain and can be easily adapted to deal with other uncertainties and applied to other supply chain problems. The optimization model provides methodological suggestions for the decision makers on the capital investment decisions and logistic decisions in the stochastic environment.

A case study of Iowa is presented to illustrate and validate this supply chain design and optimization model. The results show that uncertain factors such as biomass availability, technology advancement and biofuel price can be pivotal in this supply chain design and optimization. The locations of fast pyrolysis plants and logistic decisions are sensitive to uncertainties while the capacity levels are insensitive. In addition, farmers' participation has a significant impact on the decision making process. It is appropriate and necessary to apply stochastic programming framework to deal with the uncertainties, especially at a low farmers' participation level. As farmers' participation increase, the supply chain design and optimization model will become more profi le and more robust against the uncertainties along the supply chain.

In summary, this paper provides a modeling framework to study the advanced biofuel production pathway under uncertainty. Our study is subject to a number of limitations. Firstly, we assume the sustainability factor and farmers' participation are the same for each county. However, these factors may vary based on the land characteristics and agricultural management practices. Additional constraints such as water use constraints [50]) can be included to better describe the biomass availability. Secondly, we assume the transportation cost within counties is negligible, which could impact the supply chain design and decision making. Thirdly, we consider three sources of uncertainties and more uncertainty factors can be considered. Last but not least, only one set of scenarios is generated in this paper, more scenarios could be generated to test the stability of the stochastic results. We shall address these limitations in our future research.

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